

# Don't Let Me Down!

## Offloading Robot VFs Up to the Cloud

Khasa Gillani<sup>\*†</sup>, Jorge Martín-Pérez<sup>\*</sup>, Milan Groshev<sup>\*</sup>, Antonio de la Oliva<sup>\*</sup> and Robert Gazda<sup>‡</sup>  
<sup>\*</sup>Universidad Carlos III de Madrid, <sup>†</sup>IMDEA Networks Institute, <sup>‡</sup>Interdigital Inc.

**Abstract**—Recent trends in robotic services propose offloading robot functionalities to the Edge to meet the strict latency requirements of networked robotics. However, the Edge is typically an expensive resource and sometimes the Cloud is also an option, thus, decreasing the cost. Following this idea, we propose Don't Let Me Down! (DLMD), an algorithm that promotes offloading robot functions to the Cloud when possible to minimize the consumption of Edge resources. Additionally, DLMD takes the appropriate migration, traffic steering, and radio handover decisions to meet robotic service requirements as strict latency constraints. In the paper, we formulate the optimization problem that DLMD aims to solve, compare DLMD performance against the state of the art, and perform stress tests to assess DLMD performance in small & large networks. Results show that DLMD (i) always finds solutions in less than 30ms; (ii) is optimal in a local warehousing use case; and (iii) consumes only 5% of the Edge resources upon network stress.

**Index Terms**—robotic, optimization, offloading, Edge

### I. INTRODUCTION

NETWORKED robotic services are being adopted to enhance operational automation and performance in some uses cases, e.g., assembly robots in Industry 4.0. Networked robotic services split the functionality [1], [2] in Virtual Functions (VFs) running in servers and robots. For example, a robot driving service runs the robot drivers VF ( $v_1$ ) in the robot and the driving VF ( $v_2$ ) in a Cloud/Edge server – see Fig. 1 (a). Thus, it is necessary to decide which server will host VF  $v_2$  and the traffic steering between the robot and the server.

Deciding the VF deployment and traffic steering relates to solving the VF embedding problem. The literature tackles the VF embedding problem using artificial intelligence [3] and bin packing-alike heuristics [4]. The solutions guarantee that resources – e.g. bandwidth and CPUs – are not exhausted, and typically minimize the latency of the embedded service. Hence, traditional solutions foster deploying VFs at the Edge despite they are expensive or not.

Recent works about VF embedding of robotic services – see [1], [2], [5] – fail to consider some service requirements as the latency [1]; radio signal quality [2], [5]; or robot mobility [2]. Consequently, the robotic service may not fulfill strict [6] service latency requirements – see Fig. 1 (b)–, suffer from small bitrates, or service disruption due to bad radio connectivity/coverage – see Fig. 1 (c).

This work has been partly funded by the Spanish Ministry of Economic Affairs and Digital Transformation and the European Union-NextGenerationEU through the UNICO 5G I+D 6G-EDGEDT and 6G-DATADRIVEN.

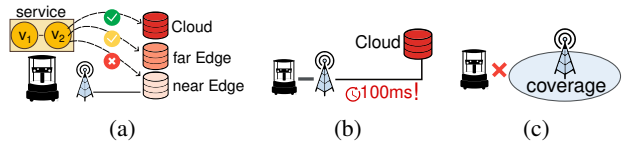


Fig. 1: Don't Let Me Down! fosters offloading the robot service VFs up to the cloud (a), yet preventing the cloud large latencies (b) and running out of coverage (c).

To address these challenges, in this paper we propose Don't Let Me Down! (DLMD). DLMD minimizes the deployment cost fostering the offload of VFs to the cheap Cloud. Additionally, DLMD considers (i) the robotic service latency constraints; (ii) the wireless connectivity; and (iii) robot mobility. In particular, DLMD takes VF migration and radio handover decisions that prevent large latencies, and out of coverage situations – see Fig. 1 (b)-(c).

### II. DON'T LET ME DOWN! PROBLEM FORMULATION

In this section we formulate the VF embedding problem that DLMD solves to take adequate offloading, migration and radio handover decisions for robotic services. We consider a hardware graph  $G$  whose vertices  $V(G)$  correspond to switches and servers. Specifically, we consider the three tiers of servers illustrated in Fig. 1a: Cloud, far Edge, and near Edge; each with decreasing latency towards the robot, respectively.

The goal of the VF embedding problem is to offload robot VFs minimizing the resource consumption at the Edge, and satisfying the robotic service constraints. In the following Sections II-A to II-D we specify the robotic service constraints, and in Section II-E we formulate the associated VF embedding problem statement, and prove its NP-hard complexity.

#### A. Robot computational constraints

The VF embedding problem must ensure that the robot VFs do not exhaust the computational resources  $C(n)$  of each server  $n \in V(G)$ :

$$\sum_{v \in a(n)} C(v) \leq C(n), \quad \forall n \in V(G) \quad (1)$$

That is, the computational requirements of all VFs  $v$  assigned to a computing node  $a(n) = \{v_1, v_2, \dots\}$  must be lower than its available computational resources  $C(n)$ . On top, it must

ensure that all VFs  $V(S_i) = \{v_1, v_2, \dots\}$  of a robotic service  $S_i$  are offloaded at some computing node  $n$ :

$$\sum_{n \in V(G)} P(v, n) \geq 1, \quad \forall S_i \in \mathcal{S}, v \in V(S_i) \quad (2)$$

with  $P(v, n) = 1$  if VF  $v$  is offloaded at the computing node  $v \in a(n)$ , and 0 otherwise. Note that we do not prevent a VF to be “replicated” – or offloaded in multiple nodes – since load-balancing may be required by some robotic services coordinating multiple robots.

### B. Network constraints

For VFs are offloaded to the Cloud or Edge servers, the robotic service traffic has to be steered across the network. The steering cannot exhaust the bandwidth  $\lambda(n_1, n_2)$  over the hardware links – i.e., edges  $E(G)$  of the hardware graph:

$$\sum_{\substack{(v_1, v_2) \\ \in a(n_1, n_2)}} \lambda(v_1, v_2) \leq (1 - \delta(n_1, n_2))\lambda(n_1, n_2), \quad \forall (n_1, n_2) \in E(G) \quad (3)$$

with  $\delta(n_1, n_2) \in [0, 1]$  the packet drop rate present at the link  $(n_1, n_2) \in E(G)$ . Specifically, all virtual links (VL) of the service  $S_i \in \mathcal{S}$  should not use all the link bandwidth  $\lambda(n_1, n_2)$ . In (3),  $a(n_1, n_2) = \{(v_1, v_2), (v_2, v_3), \dots\}$  denotes the VLs assigned/traversing the link  $(n_1, n_2)$ .

Also – inline with (2) – all the VLs  $E(S_i)$  traffic must be processed at the server(s) where the VFs are offloaded, i.e.:

$$\sum_{(n_1, n_2) \in E(G)} P(v_1, v_2, n_1, n_2) \geq 1, \quad \forall S_i \in \mathcal{S}, (v_1, v_2) \in E(S_i) \quad (4)$$

with  $P(v_1, v_2, n_1, n_2) = 1$  if the VL  $(v_1, v_2)$  is assigned to a link  $(v_1, v_2) \in a(n_1, n_2)$ , and  $P(v_1, v_2, n_1, n_2) = 0$  otherwise. Note that constraint (4) also ensures that every VL of a robotic service  $E(S_i)$  traverses at least one physical link  $(n_1, n_2)$ .

Upon the VF offloading, the VLs steering must satisfy the flow constraint [7]. That is, every switch  $w_i$  and Point of Access (PoA)  $R_i$  ingresses and egresses the same amount of traffic:

$$\sum_{\substack{(v_1, v_2) \in a(n_1, n): \\ (n_1, n) \in E(G)}} \lambda(v_1, v_2) = \sum_{\substack{(v_1, v_2) \in a(n, n_2): \\ (n, n_2) \in E(G)}} \lambda(v_1, v_2), \quad \forall n \in \{w_i\} \cup \{R_i\} \quad (5)$$

It is also important that every server  $\forall n_2 \in \{s_i\}_i$  processing VF  $v_2$  should receive the corresponding VL traffic:

$$\sum_{\substack{(n_1, n_2) \\ \in E(G)}} P(v_1, v_2, n_1, n_2) = P(v_2, n_2) \quad \forall (v_1, v_2) \in V(S_i) \quad (6)$$

otherwise, a solution of the problem may mistakenly steer the traffic to a server without VF  $v_2$  offloaded there.

### C. Robot delay constraints

To meet the latency constraints of a robotic service, it is necessary to consider both the propagation and processing delay perceived by the robot when consuming the service.

The network delay experienced by the robotic service  $S_i$  is the sum of the delay of links  $d(n_1, n_2)$  traversed by the VLs  $(v_1, v_2)$ , and the queuing delay  $\psi(n_1, n_2)$  that may be present in network:

$$d_{net}(S_i) = \sum_{(v_1, v_2) \in E(S_i)} \sum_{\substack{(n_1, n_2) \in E(G): \\ (v_1, v_2) \in a(n_1, n_2)}} d(n_1, n_2) + \psi(n_1, n_2), \quad \forall S_i \in \mathcal{S} \quad (7)$$

To compute the processing delay we resort to the M/G/1-PS expression for the average delay as it’s a common practice in the existing literature [8]–[10]. Therefore, we obtain the processing delay of a VF  $v$  as:

$$d_{pro}(v) = \sum_{(v_1, v) \in E(S_i)} \frac{1}{C(v)\mu - \lambda(v_1, v)}, \quad \forall S_i \in \mathcal{S}, v \in V(S_i) \quad (8)$$

where  $\mu$  is the processing rate of a CPU. That is, we have an M/G/1-PS system with an aggregate processing rate  $C(v)\mu$  and an arrival rate  $\lambda(v_1, v)$ , i.e., the incoming traffic to the VF  $v$ . Hence, any offloading solution must ensure that the network and processing delay remain below the requirement of the robotic service  $D(S_i)$ :

$$d_{net}(S_i) + \sum_{v \in V(S_i)} d_{pro}(v) \leq D(S_i), \quad \forall S_i \in \mathcal{S} \quad (9)$$

### D. Robot radio constraints

Since robotic services leverage wireless technologies to connect with the offloaded VFs, the offloading must prevent using radio links that cannot meet the robotic service requirements.

The first constraint to impose is that a VL  $(v_1, v_2)$  cannot traverse the link connecting the robot with the PoA  $(r_i, R_i)$  unless the robot wireless interface is attached to the PoA:

$$P(v_1, v_2, r_i, R_i) \leq \phi(r_i, R_i), \quad \forall (v_1, v_2), r_i, R_i \quad (10)$$

with  $\phi(r_i, R_i) = 1$  if the offloading solution tells the robot  $r_i$  to attach to the PoA  $R_i$ , and zero otherwise. Note that  $\phi(r_i, R_i)$  also represents the robot handover across PoAs as it moves. Any offloading solution must ensure that the robot  $r_i$  network interface is attached to one PoA  $R_i$  to have connectivity:

$$\sum_{R_i} \phi(r_i, R_i) = 1, \quad \forall r_i \in \{r_i\}, i \quad (11)$$

otherwise, any robotic service  $S_i$  will not have connection to the remote server where the VF(s) are offloaded.

Since the wireless connectivity suffers from background noise  $N$  and heavily depends on the signal strength  $\sigma_{R_i}(r_i)$ , it is necessary to account for the effective bandwidth capacity over the wireless link from the robot to the PoA  $(r_i, R_i)$ . Inline with recent works as [11], we model the wireless transmission capacity as:

$$T(r_i, R_i) = (1 - \delta(r_i, R_i))\lambda(r_i, R_i) \log_2 \left( 1 + \frac{\sigma_{R_i}(r_i)}{N} \right) \quad (12)$$

with  $(1 - \delta(r_i, R_i))\lambda(r_i, R_i)$  being the perfect conditions bandwidth over the wireless link  $(r_i, R_i)$ , considering the

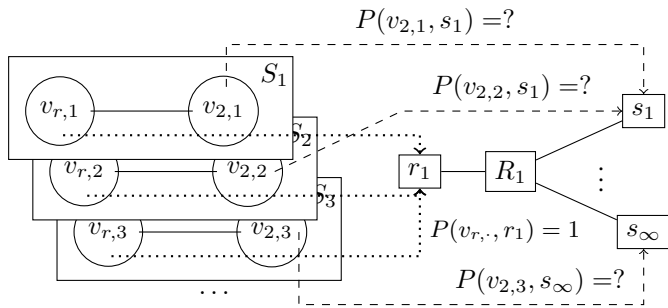


Fig. 2: VF embedding in a network with one robot  $r_1$ , one PoA  $R_1$ , and an infinite pool of servers  $\{s_i\}_i^\infty$  to decide which server we offload the second VFs  $P(v_{2,\cdot}, s_i)$  is the bin-packing problem, thus, it is NP-hard.

packet loss  $\delta(r_i, R_i)$ ; and the  $\log_2(1 + \sigma_{R_i}(r_i)/N)$  being the attenuation term under the presence of noise given a certain signal strength. Note that we assume  $N$  is additive Gaussian white noise.

Knowing the bandwidth constraint discussed in (3), if one accounts for the wireless transmission capacity  $T(r_i, R_i)$  of the link in between the robot  $r_i$  and the PoA  $R_i$ , the following must hold:

$$\sum_{(v_1, v_2) \in a(r_i, R_i)} \lambda(v_1, v_2) \leq T(r_i, R_i), \quad \forall (v_1, v_2) \in a(r_i, R_i) \quad (13)$$

so all VLs  $(v_1, v_2)$  traversing the robot-to-PoA wireless connection do not exceed the transmission capacity.

### E. Problem statement and complexity

With the prior constraints we formulate the optimization problem that captures the associated VF embedding problem. The goal is to minimize the used Edge resources, so the substrate network is shared by multiple robotic service.

#### Problem 1: VF embedding for robotic services

Given the computational (1)-(2), network (3)-(6), delay (9), and radio constraints (10), (11), (13) of a robotic service  $\mathcal{S}$ ; minimize the Edge resource usage with adequate VF offloading  $P(v, n)$ , routing  $P(v_1, v_2, n_1, n_2)$ , and attachment  $\phi(r_i, R_i)$  decisions.

$$\begin{aligned} \min_{P(\cdot), \phi(\cdot)} \quad & \sum_{n \in V(G)} \kappa_n |a(n)| \\ \text{s.t.} \quad & (1) - (6), (9) - (11), (13) \end{aligned}$$

with  $\kappa_n \in \mathbb{N}$  being the server cost, which takes higher values if the server  $n$  is closer to the Edge.

We solve Problem 1 iteratively as the robot moves. Hence, changes in  $\phi(\cdot)$ , and  $P(\cdot)$  decision variables represent handovers and VF migrations respectively. However, finding the optimal solution of Problem 1 is not straight-forward. Inline with the complexity of existing optimization problems [7], [12], in the following Lemma 1 we prove that it is NP-hard.

### Lemma 1. Solving Problem 1 is NP-hard.

*Proof.* We prove that our proposed problem is NP-hard showing that an instance of Problem 1 is equivalent to the bin-packing problem [13]. Let's consider a set of "ideal" robotic services  $\mathcal{S}'$  without any delay  $D(S_i) = \infty$ ,  $\forall S_i \in \mathcal{S}'$  and bandwidth  $\lambda(v_1, v_2) = 0$  requirements. On top, these "ideal" robotic services consist of just two VFs  $V(S_i) = \{v_{r,i}, v_{2,i}\}$ ,  $\forall S_i \in \mathcal{S}'$ , a single VL  $(v_{r,i}, v_{2,i})$  and the former VF has to run in the robot  $P(v_{r,i}, r_1) = 1$ ,  $\forall S_i \in \mathcal{S}'$  – see (Fig. 2). Hence constraints (2) and (4) are strict equalities.

Now let's assume that all these "ideal" robot services have to be deployed in a hardware graph consisting of one robot  $r_1$  with infinite computational capacity  $C(r_1) = \infty$ , a single PoA  $R_1$  that covers all the geographical area with adequate signal strength towards the robot, so  $\sigma_{R_1}(r_1) > N$  holds, and an infinite number of servers  $\{s_i\}_i^\infty$  with finite capacity  $C(s_i) < K \in \mathbb{N}^+$  and same cost  $\kappa_{n_1} = \kappa_{n_2}, \forall n_1, n_2 \in V(G)$ . All the servers have at one hop distance the PoA  $R_1$ , as shown in Fig. 2.

Hence, in the resulting scenario – depicted in Fig. 2 – the VF embedding consists in deciding where to deploy the second VF, i.e.,  $P(v_{2,i}, s_i)$ ,  $\forall S_i \in \mathcal{S}'$ . For the VL routing decision will be to traverse the single link connecting the PoA with the server, i.e.,  $P(v_{2,i}, s) = 1 \implies P(v_{r,i}, v_{2,i}, R_1, s) = 1$ ,  $\forall S_i \in \mathcal{S}'$  with  $s \in \{s_i\}_i^\infty$ . As a result, the considered "ideal" robot service leads to the following instance of Problem 1:

$$\min_{P(v_{2,i}, s)} \sum_{s \in \{s_i\}_i^\infty} |a(s)| \quad (14)$$

$$\text{s.t.} : \sum_{v_{2,i} \in a(s)} C(v_{2,i}) \leq C(s), \quad \forall s \in \{s_i\}_i^\infty \quad (15)$$

$$\sum_{s \in \{s_i\}_i^\infty} P(v_{2,i}, s) = 1, \quad \forall S_i \in \mathcal{S}' \quad (16)$$

where the bandwidth constraints (3), (5) and (13) do not apply given that  $\lambda(v_{r,i}, v_{2,i}) = 0$ ,  $\forall S_i \in \mathcal{S}'$ . Note that the radio attachment decision is given, hence, (10) and (4) are satisfied; and the delay constraint (9) is always satisfied for the "ideal" robotic service.  $D(S_i) = \infty$ ,  $\forall S_i \in \mathcal{S}'$ .

Overall, (14)-(16) is an instance of Problem 1 that is equivalent to the bin-packing problem with servers  $\{s_i\}_i^\infty$  as bins with size  $C(s)$ , and the second VFs  $v_{2,i}$  as items with size  $C(v_{2,i})$ . Therefore, Problem 1 is NP-hard.  $\square$

### III. DON'T LET ME DOWN!: THE ALGORITHM

DLMD solves Problem 1 by offloading the VFs up to the Cloud if its delay is not too large. First, DLMD selects which are the PoAs covering the robot, and offering enough wireless capacity for the first VL  $(v_1, v_2)$  – see line 1 in Algorithm 1. Second, DLMD decides to which server it should offload every VF. To do that, DLMD keeps a metric  $\tau$  representing the trade-off between the server cost  $\kappa_n$ , the free bandwidth of links to reach the server  $\frac{1}{\lambda(n_1, n_2)}$ , and the delay of such links  $d(n_1, n_2)$ . Specifically,  $\tau$  is derived using Dijkstra with weight

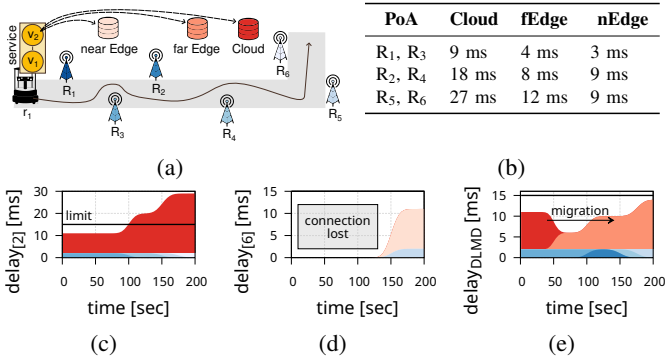


Fig. 3: Delay experienced by the robot as it drives in a warehousing scenario (a). (b) shows latencies due to queue congestion and (c)-(e) indicate the delay contribution of PoAs (blue fill) and servers (red fill) using [1], [5] and DLMD.

$1/\lambda(\cdot) + d(\cdot)$  towards the candidate servers where VF are offloaded – see line 5 of Algorithm 1.

Third, DLMD offloads the VF to the server with best  $\tau$  metric, and steers the traffic over the path found by the  $\frac{1}{\lambda} + d$ -weighted Dijkstra. Lastly, DLMD selects the PoA with highest bandwidth available and small delay to the robot – see line 12 of Algorithm 1.

#### Algorithm 1 Don't Let Me Down! (DLMD)

---

**Input:**  $G, S_i, r_i, \{R_i\}_i, \{\kappa_n\}_{n \in V(G)}$   
**Output:**  $\{\phi(r, R_i)\}_i, \{P(v_i, n_i)\}_i, \{P(v_i, v_j, n_i, n_j)\}_{i,j}$

- 1:  $\{\hat{R}_i\} = \{R_i : \lambda(v_1, v_2) \leq T(r_i, R_i)\}_i$
- 2: **for**  $v \in V(S_i)$  **do**
- 3:      $\tau_{\min} = \infty$
- 4:     **for**  $n \in V(G)$  **do**
- 5:          $\tau, p = \kappa_n + \text{Dijkstra}(n, n_{-1}, \text{weight} = \frac{1}{\lambda} + d)$
- 6:         **if**  $\tau < \tau_{\min}$  **then**
- 7:              $\tau_{\min} = \tau$
- 8:              $P(v, n) = 1$
- 9:              $\{P(v_{-1}, v, n_1, n_2) = 1\}_{(n_1, n_2) \in p}$
- 10:         **end if**
- 11:     **end for**
- 12:      $\phi\left(r, \arg \min_{\hat{R}_i} \frac{1}{\lambda(r_i, \hat{R}_i)} + d(r_i, \hat{R}_i)\right) = 1$
- 13: **end for**

---

Thanks to its trade-off metric  $\tau$ , DLMD will always try to offload the VFs to the Cloud unless there are Edge servers with significantly smaller latency and leaves as much free resources in the Edge as possible – thus, minimizing Problem 1 objective – and steer the traffic over non-congested links. DLMD is invoked iteratively to update the offloading  $P(\cdot)$  and attachment/handover  $\phi(\cdot)$  decisions as robot moves.

## IV. EXPERIMENTAL RESULTS

In this section we assess DLMD performance in two scenarios: (i) a small warehousing scenario taking VF offloading, migration, and handover decisions; and (ii) a stress test in small and large graphs with real-world PoA locations.

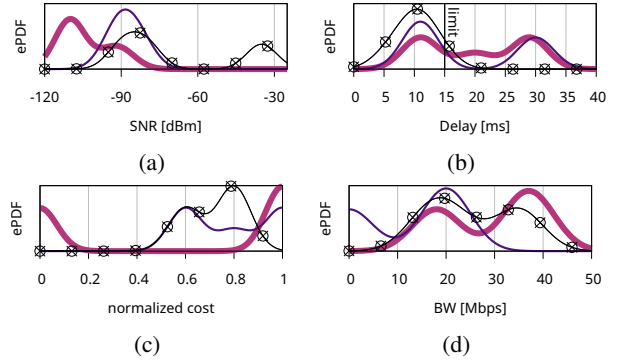


Fig. 4: ePDFs for the experienced SNR, Delay, cost, and bandwidth consumption during Fig. 3a driving. Plots illustrate the experienced metrics using DLMD (circle), optimal (cross), [1] (thickest), and [5] (thick)

### A. Small warehousing scenario

We consider a factory floor with a warehousing robot service  $S_1$  that offloads its remote driving VF  $v_2$  to a near/far Edge or Cloud server – with light-, mid- and intense-red in Fig. 3a; respectively. As the robot moves, DLMD must decide to which PoA  $R_1, \dots, R_6$  (blue color) it should attach, and make the corresponding offloading and migration decisions for the remote driving VF  $v_2$ . Note that the robot drivers VF is denoted as  $v_1$  and they reside in the robot in the considered experiment. The initial offloading, migration and handover decisions must be such that the service latency remains below the  $D(S_1) = 15$  ms requirement of the considered warehousing service. Fig. 3b reports the different average delays that each PoA has towards the servers. Figs. 3c-3e show the delay experienced by the warehousing robot during its trajectory when we use [1], [5] and DLMD; respectively.

Results show that ignoring the links' delay information – as done in [1] – violates the 15 ms limit when the robot is half-way to the end of its trajectory (100 sec.) because it connects to PoAs  $R_5, R_6$  with high latency towards the Cloud server where  $v_2$  is offloaded – see Fig. 3c. When we ignore radio signal information – as in [5] – the robot lost connectivity during the first 125 sec. – see Fig. 3d. The reason is that [5] neglected the bad SNR of the PoAs, and resulted into trying to steer traffic over wireless links without enough capacity due to the bad signal conditions.

The aforementioned problems were not experienced by DLMD – see Fig. 3e –, for it instructs the robot to attach to PoAs with adequate radio conditions, and migrated the remote driving VF  $v_2$  to the far Edge when the robot attached to PoAs with high latency towards the Cloud to meet the 15 ms limit.

For the sake of comparison, in Fig. 4 we report the ePDF of different metrics considered in the problem. Overall, results show that DLMD attains better SNR than [1], [5] and remains below the 15 ms delay limit. Moreover, DLMD matches the metrics achieved by the optimal solution – see how circle and cross markers overlap in Fig. 4. In terms of cost and bandwidth

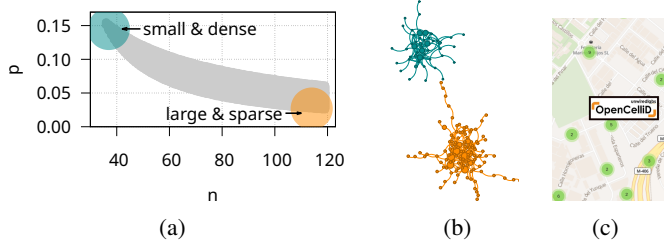


Fig. 5: Erdős–Rényi setups (a) for realistic network graphs (b) that connect OpenCellID PoAs of an industrial area (c).

consumption, DLMD achieves a nice trade-off with respect to other solutions because it only migrates resources to the expensive Edge when needed.

### B. Stress Tests

In this section we assess DLMD performance upon scarce of network resources, i.e., when the network is stressed. To do so, we collect the PoAs present in an industrial area of Alcorcón, Spain; and generate a small & large random graph that conveys the network topology – see Fig. 5.

Specifically, we derive  $V(G)$  using Erdős–Rényi  $G(n, p)$  graphs with  $n = 48, 128$  nodes; and find adequate  $p$  to have: 6 Cloud servers with 6; 4 far Edge servers with 4; and 2 near Edge servers with 2 redundant links. With this information, it is possible to find feasible  $(n, p)$  setups – see Fig. 5a gray region – knowing that  $\mathbb{P}(\text{deg}(v) = k) = \binom{n-1}{k} p^k (1-p)^{n-1-k}$ .

Fig. 6 shows how DLMD behaves as the network usage/stress evenly increases from 0 to a 100% in small & dense graphs (green), and large & sparse graphs (orange). In the experiment we use an enriched robot service with 3 VFs being offloaded to remote servers. As the robot moves along the 12 PoAs taken from OpenCellID, DLMD performs migrations and handover decisions to keep an adequate connectivity between the robot and the offloaded VFs.

Fig. 6a evidences that DLMD meets the delay service requirement of 15ms as long as network stress is below 40%. In smaller and dense graphs, the delay requirement is satisfied even with 60% stress as it has higher migration success thanks to the graph density – see Fig. 6c.

Lastly, it is worth mentioning that during the experiments DLMD uses less than a 5% of the available Edge resources, for it exploits the Cloud as long as it is close enough and available – see Fig. 6b. Moreover, DLMD managed to find solutions in less than 30 ms in both small and large graphs – see Fig. 6d.

## V. CONCLUSION

In this paper we present DLMD, an offloading algorithm for networked robotics that fosters offloading VFs to the Cloud to minimize the Edge usage. Additionally, DLMD assists in the VF migration and radio handover as the robot moves. Results demonstrate that DLMD (i) outperforms state of the art solutions in small warehousing scenarios; (ii) takes

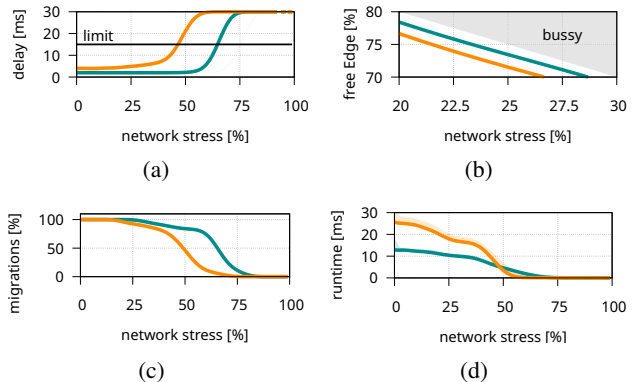


Fig. 6: DLMD stress test in Fig. 5 small (green) and large (orange) networks. Tests show 90% confidence intervals (shade).

$\leq 30$ ms to find solutions in small and large graphs with real-world PoA locations; and (iii) achieves the goal of minimizing resource consumption at the Edge despite the network stress. To the best of our knowledge, this is the first work to consider latency, radio signal, and robot mobility simultaneously to tackle the VF embedding problem. Future work will focus on the impact of robot mobility models and heterogeneous server cost. Additionally, we will further investigate a weighted  $\frac{1}{\lambda} + d$  metric for DLMD.

## REFERENCES

- [1] C. Delgado *et al.*, “OROS: Orchestrating ROS-driven Collaborative Connected Robots in Mission-Critical Operations,” *IEEE*, 2022.
- [2] W. Chen *et al.*, “QoS-aware robotic streaming workflow allocation in cloud robotics systems,” *IEEE transactions on services computing*, vol. 14, no. 2, 2018.
- [3] Y. Xiao *et al.*, “NFVdeep: Adaptive Online Service Function Chain Deployment with Deep Reinforcement Learning,” in *2019 IEEE/ACM 27th International Symposium on Quality of Service (IWQoS)*, 2019.
- [4] Y. Mao, X. Shang, and Y. Yang, “Joint resource management and flow scheduling for SFC deployment in hybrid edge-and-cloud network,” in *IEEE INFOCOM 2022-IEEE Conference on Computer Communications*. IEEE, 2022.
- [5] B. Németh *et al.*, “Delay and Reliability-Constrained VNF Placement on Mobile and Volatile 5G Infrastructure,” *IEEE Transactions on Mobile Computing*, vol. 21, no. 9, 2022.
- [6] 3GPP, “Service requirements for cyber-physical control applications in vertical domains,” 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 22.104, 21 2021.
- [7] H. Feng *et al.*, “Approximation algorithms for the NFV service distribution problem,” in *IEEE INFOCOM 2017 - IEEE Conference on Computer Communications*, 2017.
- [8] R. Cohen *et al.*, “Near optimal placement of virtual network functions,” in *IEEE INFOCOM*, 2015.
- [9] F.B. Jemaa, G. Pujolle, and M. Pariente, “QoS-aware VNF placement optimization in edge-central carrier cloud architecture,” in *2016 IEEE Global Communications Conference (GLOBECOM)*. IEEE, 2016.
- [10] D.B. Oljira *et al.*, “A model for QoS-aware VNF placement and provisioning,” in *2017 IEEE Conference on Network Function Virtualization and Software Defined Networks (NFV-SDN)*. IEEE, 2017.
- [11] L. Bonati *et al.*, “CellOS: Zero-touch Softwarized Open Cellular Networks,” *Computer Networks*, vol. 180, 2020.
- [12] Y. Sang *et al.*, “Provably efficient algorithms for joint placement and allocation of virtual network functions,” in *IEEE INFOCOM*, 2017.
- [13] Garey, Michael R. and Johnson, David S., *Computers and Intractability: A Guide to the Theory of NP-Completeness*. USA: W. H. Freeman & Co., 1990.